

EnhancedSD: Downscaling Solar Irradiance from Climate Model Projections

Nidhin Harilal¹, Bri-Mathias Hodge^{1,2}, Claire Monteleoni¹, Aneesh Subramanian¹

nidhin.harilal@colorado.edu

¹University of Colorado, Boulder

²National Renewable Energy Laboratory (NREL)

GCM (General Circulation Model)

- GCM is an attempt to augment Earth's atmosphere, using which various climate projections are generated.
- GCMs are run at low-resolution which leads to projections too coarse for assessing the localized affects.

Climate Reanalysis

- Reanalysis data provide the most complete picture currently possible of past weather and climate.
- They are globally complete and consistent in time and are sometimes referred to as '*maps without gaps*'.

Motivation

- The lack of high-resolution climate datasets is the largest impediment to mitigating impacts of climate change-induced events.
- **Statistical downscaling** techniques are used to mitigate the low spatial resolution of climate model outputs by learning a functional form to map coarsened version to fine-scale climate data (similar to image super-resolution).
- Applications like Power system planning has traditionally relied on historical climate data to plan future generation, implicitly assuming a stationary climate.

Dataset

- We perform our study over continental United States (CONUS), where historical data for supervised training purposes is relatively rich.
- **Coarse-resolution:** Climate model outputs of the solar radiation field from IPSL¹ Phase 6 of the Coupled Model Intercomparison Project (CM6A)
- **High-resolution** Downward solar radiation fields from ERA5² reanalysis.

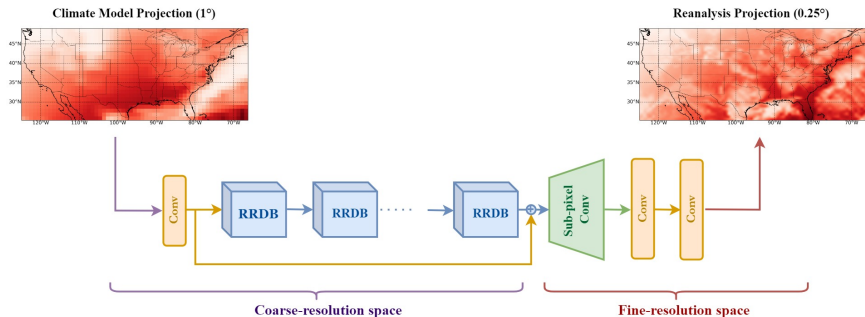
	IPSL	ERA-5
Years-range	1950-2014	1978-2022
Shape	24×59	96×236
Spatial res.	1°	0.25°
Temporal res.	3-hourly	1-hourly

Dataset Statistics

¹IPSL: Institut Pierre-Simon Laplace

²ERA5: European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis V5

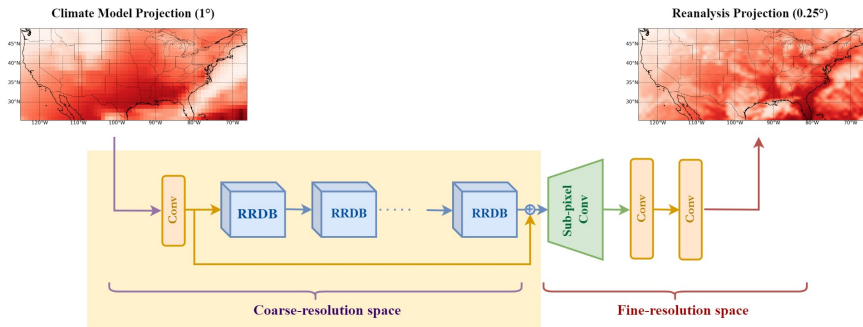
Model Description



We consider following two pathways:

- Learning in coarse-resolution space (1°).
- Learning in fine-resolution space (0.25°).

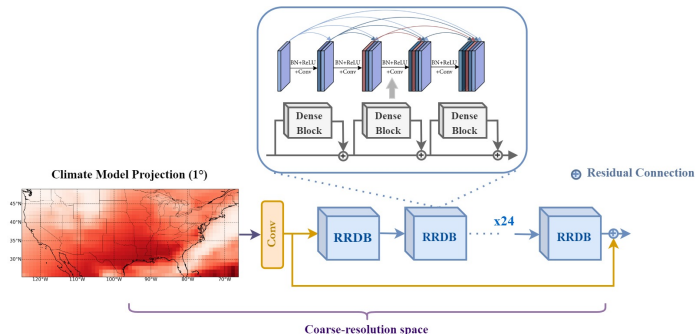
Model Description



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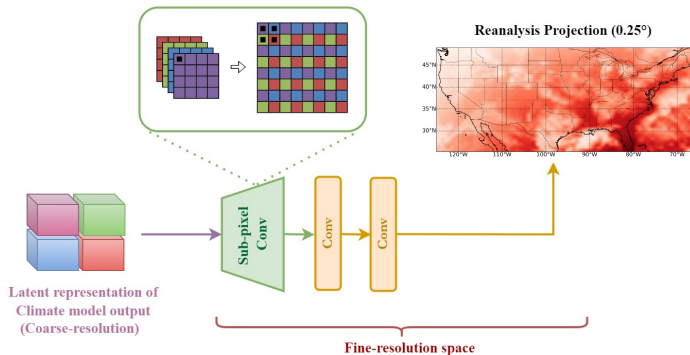
- Learning in coarse-resolution space (1°).
- Learning in fine-resolution space (0.25°).

Coarse-resolution pathway



- **RRDB (Residual-in-Residual Dense Block):**
To learn coarse-scale latent representations from climate model outputs for downscaling.

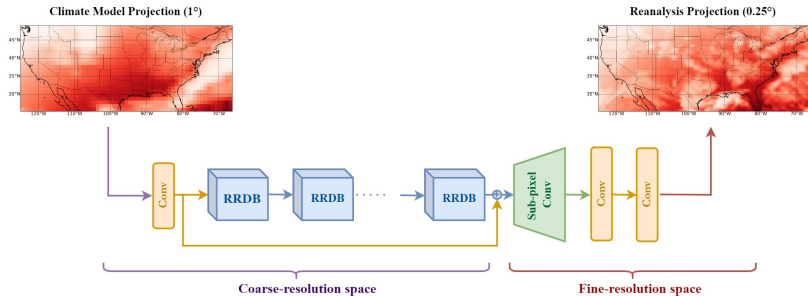
Fine-resolution pathway



- **Sub-pixel convolution:**

Maps coarse-scale representations to a fine-resolution same as the final reanalysis output.

Optimization



We optimize EnhancedSD on a weighted combination of root-mean-squared error (RMSE) and Structural Similarity Index Measure (SSIM):

$$\text{Joint Loss} = \text{RMSE} + \alpha \times (1 - \text{SSIM})$$

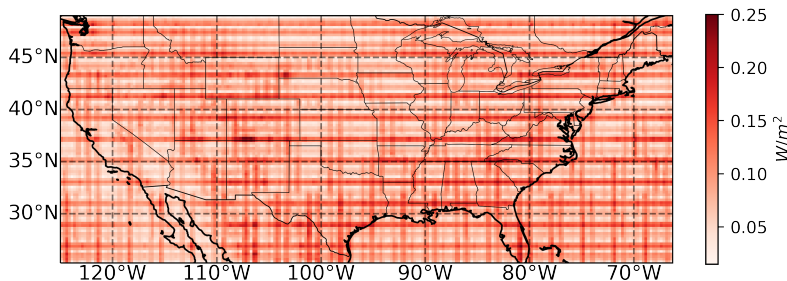
Results

		RMSE	
		Capacity	
		↓	SSIM ↑
Bicubic intep.		0.1584	0.508
EnhancedSD	w/o RRDB	0.1329	0.618
	w/o sub-pixel	0.1121	0.632
	w/o res-scaling	0.1107	0.641
	w/o SSIM	0.1083	0.647
	Proposed	0.1071	0.691

Results on downscaling solar-irradiance.

- We compare EnhancedSD and its ablations with bicubic interpolation - a standard baseline used in the super-resolution literature.

Results



- RMSE computed at each location using EnhancedSD with deconvolutions over test-period, showing the checkerboard error pattern.

Conclusion

- EnhancedSD addresses a major limitation with existing SD approaches, which do not account for the inherent domain-gap between climate model outputs and reanalysis.
- In addition to solar power datasets, EnhancedSD could be applied to generate future high-resolution reanalysis predictions from other coarse-resolution climate model outputs such as precipitation, surface temperature, etc.
- We believe that additional investigation into the methods for generating future reanalysis have a huge potential to inform climate change adaptation strategies.

The End